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IDENTIFICATION AND INTERPRETATION OF PATTERNS IN ROCKET ENGINE DATA

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Identification and Interpretation of Patterns
in
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Technical Objective:

The goal of our research is to analyze ground test data, to identify patterns associated with the anomalous engine behavior. On the basis of this analysis, it is the task of our project to develop a Pattern Identification and Detection System which detects anomalous engine behavior in the early stages of fault development significantly earlier than the indication provided by either redline detection mechanism or human expert analysis. Early detection of these anomalies is challenging because of the large amount of noise presence in the data. In the presence of this noise, early indication of anomalies becomes even more difficult to distinguish from fluctuations in normal steady state operation.

Progress:

The neural networks method have been applied in this period to supplement the statistical method (Ref. 1) utilized previously to investigate the feasibility in detecting anomalies in turbopump vibration of SSME. The anomalies are detected based on the amplitude of peaks of fundamental and harmonic frequencies in the power spectral density. These data are reduced to the proper format from sensor data measured by strain gauges and accelerometers. Both statistical and neural network methods are feasible to detect the vibration anomalies. The statistical method requires sufficient data points to establish a reasonable statistical distribution data bank. This method is applicable for on-line operation. The neural networks method also needs to have enough data basis to train the neural networks. The testing procedure can be utilized at any time so long as the characteristics of components remain unchanged.

The feasibility study for detecting anomalies in turbopump vibration data has been conducted with data from ground tests 902-473, 902-501, 902-519, and 904-097 of the Space Shuttle Main Engine (SSME). The study has been designed to analyze vibration data from each of the following SSME components: high-pressure oxidizer turbopump, high-pressure fuel turbopump, low-pressure fuel turbopump, and preburner boost pump. The pre-processor module of the software system locates and classifies peaks in the power spectral density of each 0.4-sec window of steady-state data. Peaks which represent fundamental and harmonic frequencies of both shaft rotation and bearing cage rotation are identified by the module. Based the statistics and neural networks methods, anomalies are then detected by the amplitude of each of these peaks individually.

Using the statistical method, anomalies are detected on the basis of two thresholds set individually for the amplitude of each of these peaks: a prior threshold used during the first group of windows of data in a test, and a posterior threshold used thereafter. In most cases the anomalies detected by the statistics agree with those reported by NASA as given in Ref. 2.

Using the neural networks, the amplitude of each of these peaks are selected as input training data sets including normal and abnormal samples in a single test. The reserved testing data which have not been used to training the network in the same test are applied to assess the effectiveness and feasibility of the neural network approach. The HPFTP is the selected component for the current study. The rate of correct diagnosis to identify the normal or abnormal conditions is better than 95% of the total testing cases.

Current Systems

The prototype software systems have been designed for detecting anomalies in turbopump vibration data from ground tests of SSME by using the statistics and neural networks. The sensor data pre-processor module is described in the following sections.

Sensor Data Pre-processor

Vibration data was provided by NASA in the form of FFT from accelerometers mounted on the oxidizer and fuel pumps. A set of Fortran programs running on the UTSI VAX 11/780 has been developed to read these data tapes in NASA binary format which is inherently machine-dependent, to swap bytes from the NASA binary format to the VAX internal binary representation, and to convert the data into a portable ASCII format. After initial preprocessing on the VAX, the power spectra are stored in a form which can be quickly sent to any other platform at UTSI.

The **Frequency Extractor** is designed to identify the fundamental and harmonic frequencies of both shaft rotation and bearing cage rotation in each FFT window. Firstly peaks representing candidates for the shaft fundamental are reliably found based on an empirical linear fit, for each

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type of turbopump, of shaft rotation speed to SSME power level. The actual shaft and cage fundamental and their harmonics are then identified based on the ratio of cage to shaft rotation and the required consistency among the different harmonics of both shaft and cage. Freq-Extra is also designed to detect the intermittent frequencies whose amplitudes are above a specific value i.e. noise-level.

The typical data histogram of synchronous frequency plotted as the number density distribution from 1500 to 3900 units amplitude from 110 windows during the time period of 169 sec. to 213 sec. is shown in figure 1. The typical data histogram of 240-hz from sensor 686 & 698 is shown in figure 1. The data from sensor 613 shown in figure 2 are synchronous and sub-synchronous frequencies. All distribution is close to a 'normal Gaussian' function. The 2nd, 3rd and 4th harmonics also have the similar distribution. Thus, the statistic mean and standard deviation of the data distribution are useful as the benchmark for the anomalies detection.

The overall results assure us that the statistical strategy for detecting anomalies works reasonably well for most cases tested as given in the previous semi-annual report (Ref. 1) and an AIAA conference paper (Ref. 3).

Neural Networks Diagnosis

For a specific turbopump component, the fundamental frequency and harmonics for the normal and abnormal conditions have their distinct characteristics as shown in Figure 3 and 4. The neural networks algorithm is a powerful pattern recognition method. Thus, the application of the neural nets techniques to the HPFTP's data from test 501 and 519 allows us to examine the feasibility in diagnosing the anomalies.

Neural Network Algorithm Description. A three-layer Back-Propagation (BP) Neural Network has been selected for the present study. Multilayer BP networks have been studied extensively and are widely used for pattern classification. Multilayer networks are able to classify non-linearly separable classes. In the present case, a three layer network is utilized including input layer, hidden layer and output layer. A 3-layered (input, hidden,output), fully connected, feed-forward network as shown in figure 5. The normalized data sets are utilized. Both input and output are continuous-valued (between -0.5 and 0.5) vector. The outputs generated by the network are compared with the desired or target outputs. Errors are computed from the differences, and the weights are changed in response to these error signals as dictated by the Generalized Delta Rule (Ref. 4). Thus, a BP network learns a mapping function by repeatedly presenting patterns from a training set and adjusting the weights. A commercial neural network program named ANSim (Ref. 5) is utilized for the training process as well as the testing process.

The Training Procedure is in the iterative fashion. It loops repeatedly over the set of training patterns until the total root mean square (RMS) error for all patterns is less than the specified value, e.g. 0.1. The Testing Procedure is forward feed processing.

Neural Network ANSim Software. SAIC ANSim 2.30 (Ref. 5) is a graphics oriented, menu-based artificial neural system (ANS) simulation program, which provides a complete complement of neural model development, allocation and analysis capabilities, including a powerful ANS creation, training, execution and monitoring tool. ANSim enables users to quickly implement and utilize ANS models using 13 paradigms such as Back Propagation (BP), Hopfiled Network, etc. ANSim enables the user to configure any number of ANS neural networks. It drives each network with a sequence of training and/or input data. For each model, ANSim will (1) monitor the response, (2) capture the output, and (3) save the configuration for later re-use. ANSim is integrated under Microsoft Windows to provide an effective, easy-to-use interface.

Floating Point Processor for ANSim. A PC 386 (VGA or EGA monitor) with the SAIC's Delta Floating Point Processor, which is a 22 MFlop AT bus compatible processor, allows for high speed Neural Network Systems training and processing.

Sample Data in the Form of Spectrum Plots. The typical data sets are obtained by the pre-processor module as shown in Fig. 3. consisting of synchronous frequency samples of normal and 240-hz abnormal data sets for sensor 696 and 698. The sensor 617 for Synchronous and Sub-synch frequency data is shown in Fig. 4. The reserved testing data shown in figures 3 & 4, which have not been used for training the network in the same test, are applied to assess the effectiveness and feasibility of the network approach.

Results of Neural Networks. The initial selected component for the current study is the HPFTP. The vibration data from ground tests 902-501 and 902-915 for the HPFTP as shown in figure 3 & 4 are utilized to the current vibration anomalies detection. The successful detection rate is higher than 95% to identify either normal or abnormal running condition. The results have indicated that the application of Neural Network to the available SSME vibration data sets in diagnosing existing faults in the data is a viable method.

Moreover, the actual clock time of computer computation on a PC-386 with Floating Point Processor are less than 1 minutes for the training process. The testing time of the feed-forward process is near real time in the present case. This is important to know this computation time for planning on-line or off-line operation in addition to its ability to identify the correct anomalies.

Summary

Automatic detection of anomalies in Space Shuttle Main Engine Turbopumps has been implemented as a prototype software system on a Symbolics 3670 lisp machine and on a PC. The system has demonstrated its capability in detecting anomalies in turbopump vibration data earlier than the indication provided by the redline detection mechanism. The present statistical strategy based on the distribution of data in detecting anomalies for SSME turbopumps seems to work well, even though some limited cases require further study. On the other hand, the limited application of neural networks to the HPFTP has also shown the effectiveness and
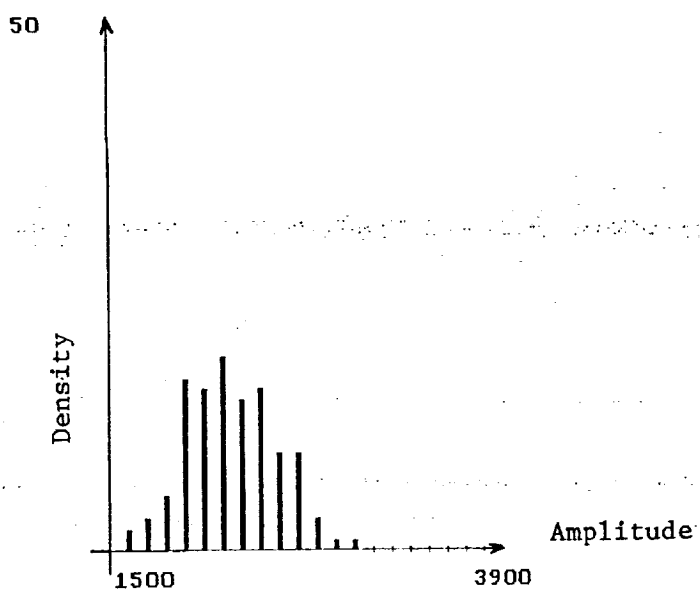
feasibility to diagnose the anomalies of turbopump vibrations. The further investigation on data from a numerical simulator is warranted.
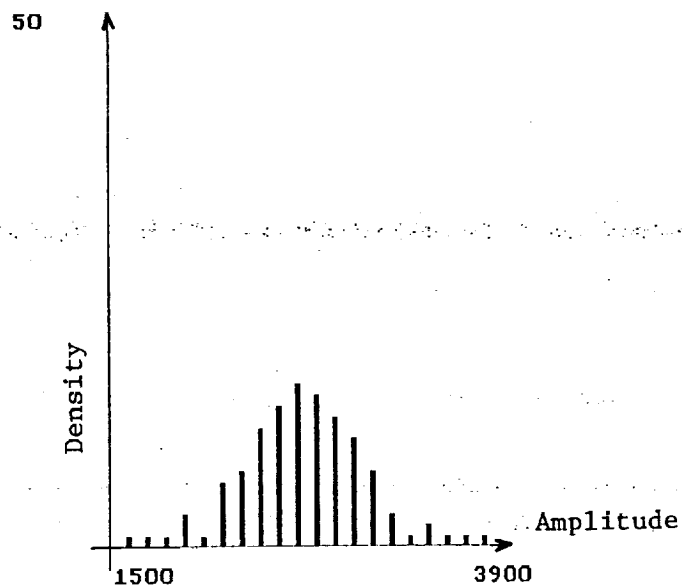
Future Work:

The satisfactory results given by the neural network approach can be reassured to investigate more cases and more fault scenarios. Since the ground testing data are limited, we decide to use the data generated from a NASA/MSFC's numerical simulator for the follow-on study. The support of the data from the NASA/MSFC simulator are critical to the success of completion of this endeavor.

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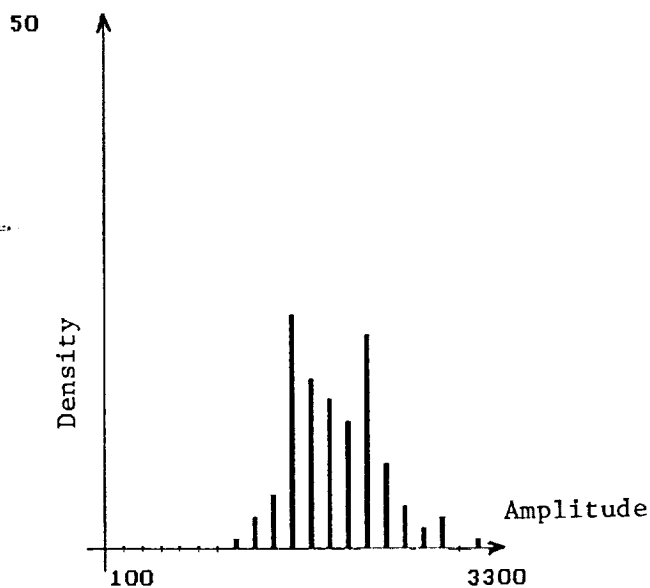
T9020501 Sensor 696: 169.0-213.0 Sync
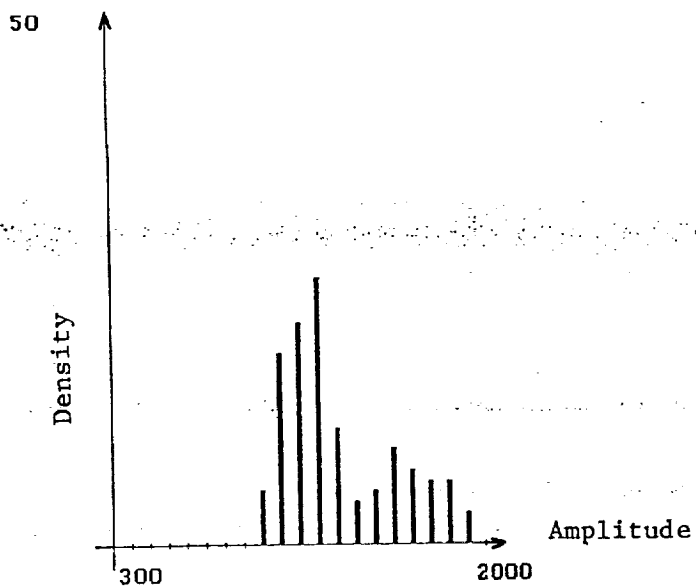
T9020501 Sensor 698: 169.0-213.0 Sync

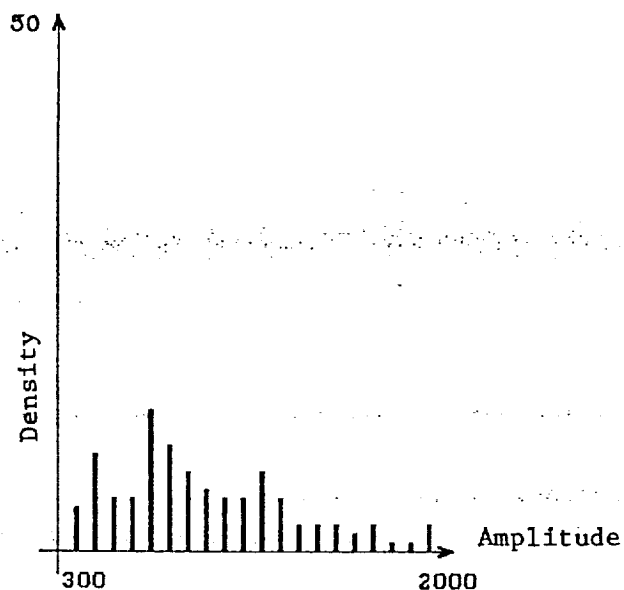T9020501 Sensor 696: 169.0-213.0 240HZ
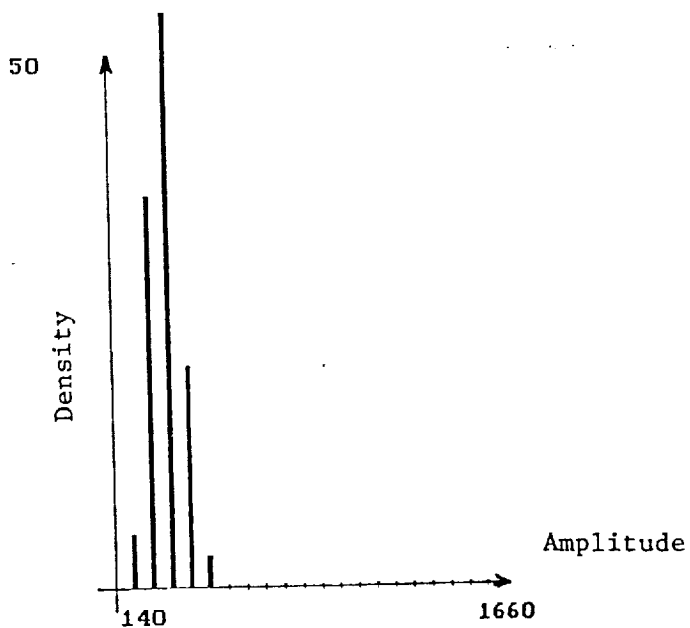
T9020501 Sensor 698: 169.0-213.0 240HZ

Figure 1.   Data Histogram of Synchronous Frequency and 240-hz Frequency
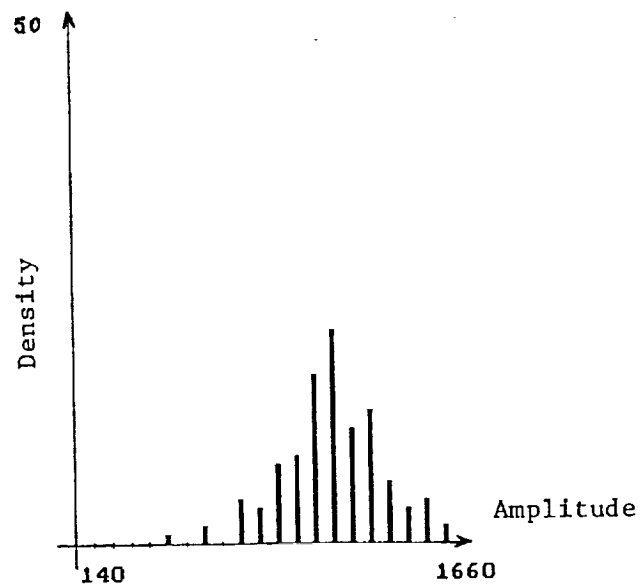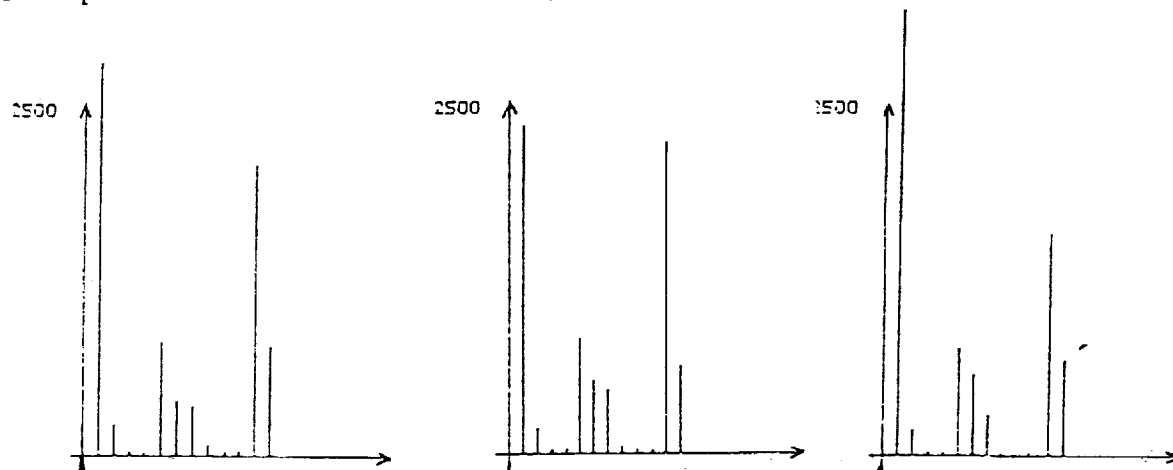from Sensors 696 and 698.

Figure 2. Data Histogram of Synchronous Frequency and Sub-synchronous
Frequency from Sensor 613.

3 samples of Normal Data: (USED FOR TRAINING)

3 samples of 240HZ Abnormal Data: (USED FOR TRAINING)

3 Samples of Testing Data:(Sensor 697 FASCOS-HPFP of Test 9020501 at 109%)

At 192.6 Sec
Normal.

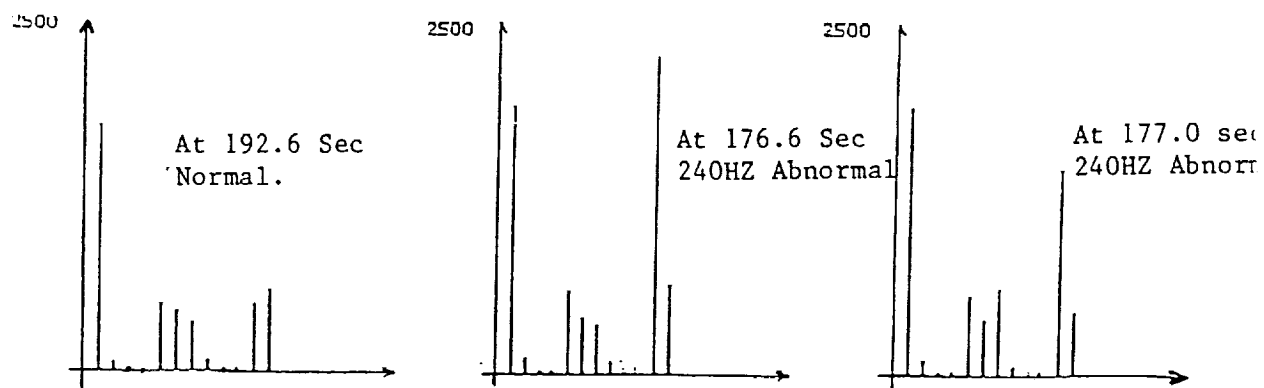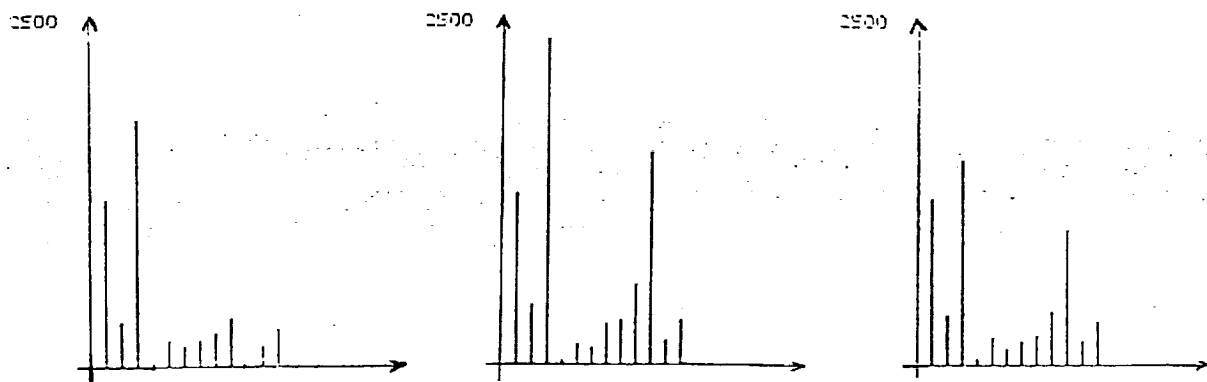At 176.6 Sec
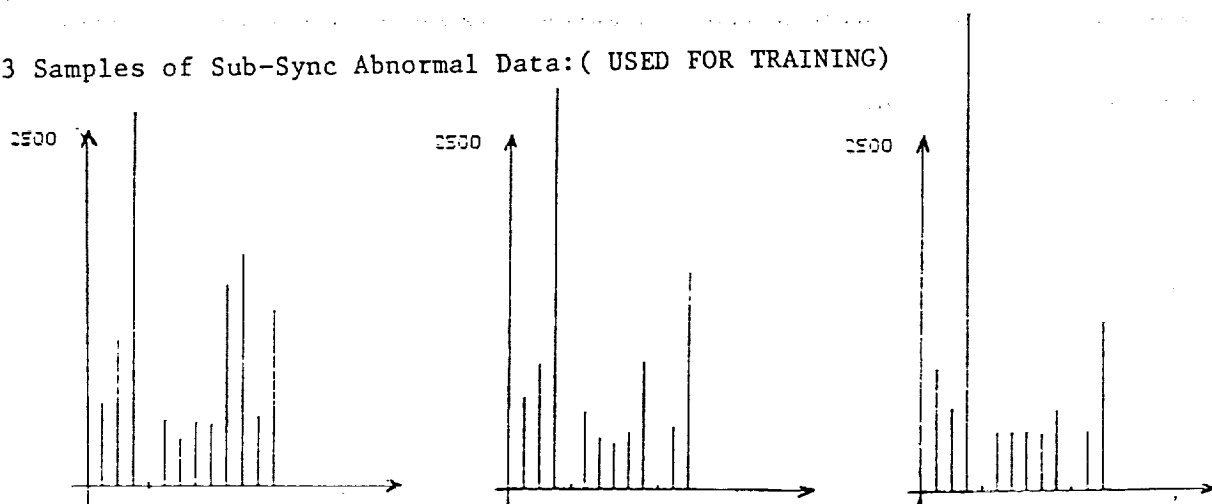240HZ Abnormal

At 177.0 sec
240HZ Abnorm

Figure 3.   Samples of Normal and 240-hz Abnormal Data from HPFTP Sensors
of Test 902-501 at the Thrust-level 109%.

3 Samples of Normal Data :(USED FOR TRAINING)

3 Samples of Sub-Sync Abnormal Data:(USED FOR TRAINING)

3 Samples of Testing Data:(Sensor 617 HPFP-RAD-180 of Test 9020519 at 109%)
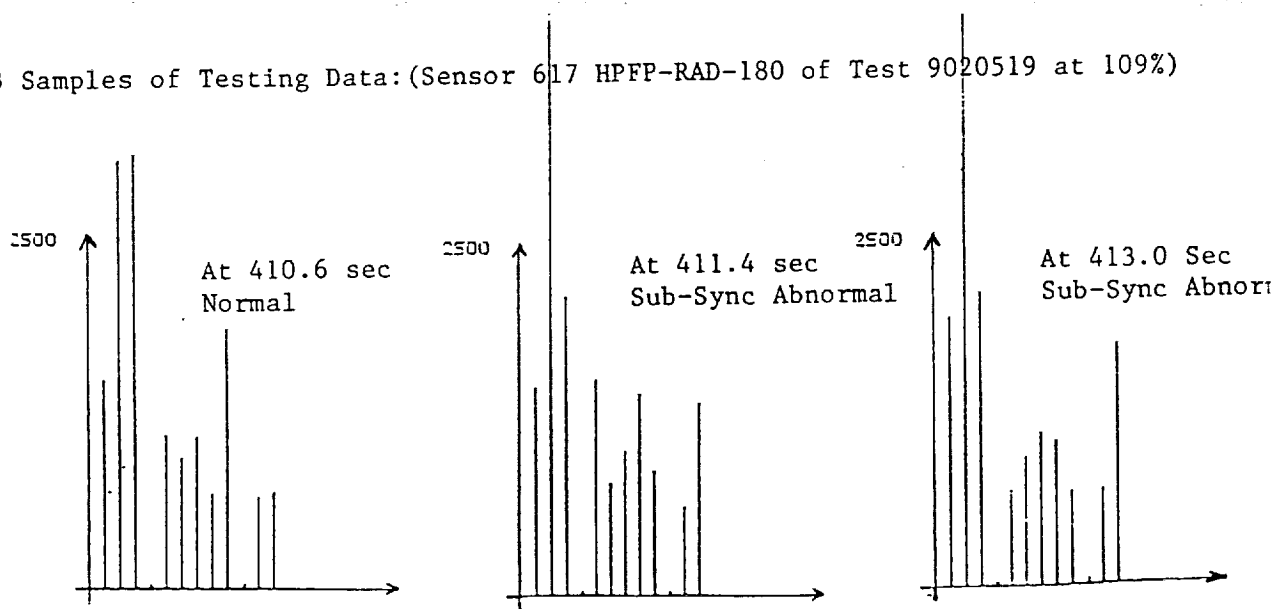
At 410.6 sec
Normal

At 411.4 sec
Sub-Sync Abnormal

At 413.0 Sec
Sub-Sync Abnor

Figure 4. Samples of Normal and Sub-synchronous Abnormal Data from
          HPFTP Sensors of Test 902-519 at the Thrust-level 109%.

Input Layer

(13 nodes : Shaft fundamental
            Shaft fundamental's three harmonics
            cage fundamental
            Cage fundamental's three harmonics
            Inner race,outer race,240HZ,Sub-sync
                                        thrust-level)

Hidden Layer

(6 nodes)

Output Layer

(2 nodes: for FASCOS-HPFP, normal & 240HZ abnormal
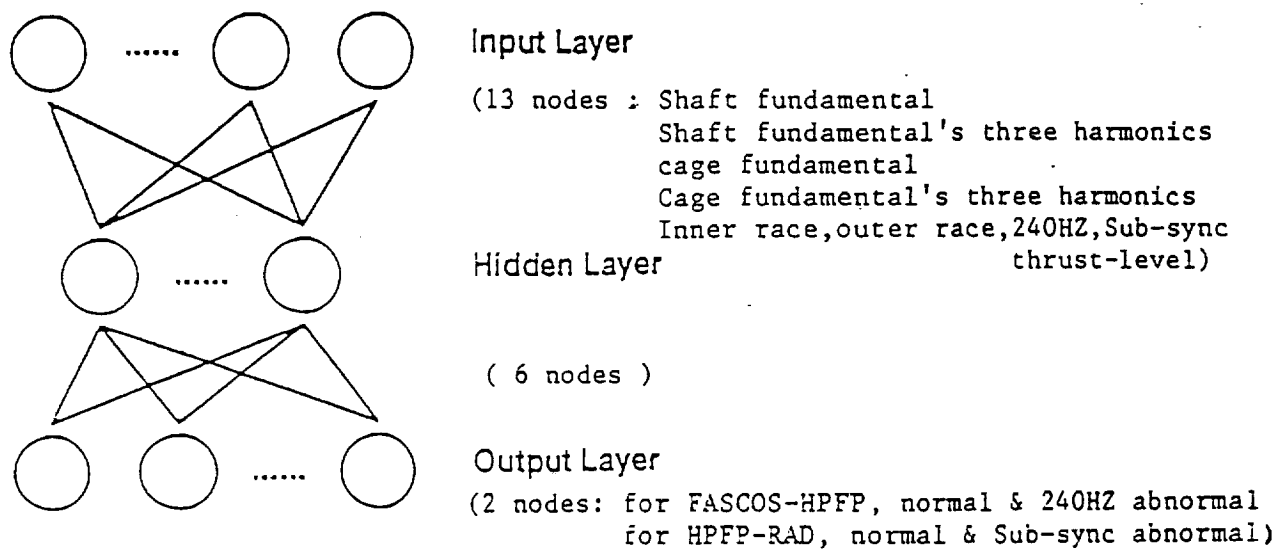   for HPFP-RAD, normal & Sub-sync abnormal)

Figure 5.   Three-layer Back-propagation Neural Network Architecture.